Low-Cost Smartphone-based Plant Disease Diagnosis for Zimbabwean Farmers using Transfer Learning and Crowdsourced Image Data

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ABSTRACT

Timely and accurate identification of crop diseases is vital for improving food security and farmer livelihoods, particularly in low-resource agricultural settings. This study presents a low-cost, smartphone-compatible plant disease diagnosis system designed specifically for Zimbabwean farmers. The system integrates transfer learning with the MobileNetV2 architecture and leverages a hybrid dataset composed of curated PlantVillage images and 400 crowdsourced leaf images collected from smallholder farmers in Zimbabwe. Following preprocessing and augmentation, the data was used to train a lightweight convolutional neural network via a two-stage transfer learning approach. The model achieved a test accuracy of 91.0%, with strong precision, recall, and F1-scores across six classes. A web-based prototype was developed using Streamlit and deployed via Ngrok, allowing real-time disease prediction through browser-based image uploads, simulating field use on mobile devices. Compared with previous studies, this work demonstrates competitive accuracy while emphasizing practical deployability and contextual relevance. The inclusion of locally sourced images significantly improved real-world performance. The approach empowers Zimbabwean farmers with rapid, accurate, and actionable plant disease diagnosis, supporting sustainable agriculture and food security.

Keywords

Plant disease diagnosis; transfer learning; MobileNetV2; crowdsourced dataset; Zimbabwe; Streamlit.

1. INTRODUCTION

Plant diseases represent a significant challenge to agricultural productivity worldwide, particularly in developing countries like Zimbabwe where smallholder farmers rely heavily on crop yields for food security and income [1]. Moreover, agriculture forms the backbone of Zimbabwe's economy, employing over 70% of the population and contributing approximately 17% to the national GDP [2]. Smallholder farmers, who cultivate crops such as maize, tobacco, and tomatoes on limited land, are particularly vulnerable to plant diseases, which cause significant yield losses estimated at 20–40% annually [3]. These diseases exacerbate food insecurity, economic hardship and threatening livelihoods and progress toward Sustainable Development Goal 2 (Zero Hunger).

Early and accurate diagnosis of plant diseases is critical to mitigating crop losses and ensuring sustainable agricultural practices. However, traditional methods of disease identification—such as expert field inspections and laboratory analysis—are often inaccessible to many farmers due to cost, limited availability of specialists, limited infrastructure, logistical challenges and delayed results [4]. These constraints highlight the urgent need for affordable, rapid, and scalable diagnostic solutions tailored to local contexts. Also, with Zimbabwe's rural smartphone penetration reaching 97.5% in 2023 [5][6], there is untapped potential to leverage mobile technology for affordable, scalable plant disease diagnosis.

Recent advances in artificial intelligence (AI), especially deep learning techniques like convolutional neural networks (CNNs), have demonstrated remarkable success in image-based plant disease detection [7] [8]. By training models on large datasets of diseased and healthy plant images, AI systems can identify disease symptoms with high accuracy and speed, even under varying environmental conditions [9]. Transfer learning, which adapts pre-trained models to new, domain-specific datasets, further enhances the feasibility of deploying these systems in resource-constrained settings by reducing the need for extensive labeled data [8] [10].

Simultaneously, the widespread adoption of smartphones in Zimbabwe provides an accessible platform to deliver these AI-powered diagnostic tools directly to farmers. Even low-cost smartphones are now capable of running lightweight machine learning models, enabling farmers to access smart solutions without needing expensive hardware. This opportunity opens the door to delivering AI-driven plant disease diagnosis through mobile platforms, even in offline rural settings. Therefore, this article proposes a low-cost, smartphone-compatible, web-based plant disease diagnosis system for Zimbabwean farmers that leverages transfer learning and crowdsourced image data. The approach leverages crowdsourced leaf image data and transfer learning to build an accurate yet computationally efficient diagnostic model. By integrating crowdsourced data collection, the platform also supports continuous model refinement and adaptation to local disease patterns, ensuring sustained relevance and effectiveness [11]. The system empowers farmers with timely, accurate disease identification and treatment recommendations, facilitating proactive crop management and improved agricultural productivity.

Several recent studies and projects underscore the potential of such web-based AI systems. For example, a web-based tomato plant disease detection system using CNNs demonstrated accurate and timely diagnosis through an intuitive interface accessible on smartphones, helping farmers mitigate crop losses and promote sustainable farming practices [12]. Similarly, AI-powered platforms combining disease detection with real-time advisory chatbots have enhanced user engagement and decision-making support in agriculture [13]. These precedents validate the approach of combining transfer learning, crowdsourced data, and web technologies to address plant disease challenges in low-resource environments.

In summary, this work aims to develop and deploy a scalable, user-friendly, web-based plant disease diagnostic tool tailored to the needs of Zimbabwean farmers, harnessing the power of transfer learning and community-driven data to improve disease management and food security.

2. LITERATURE REVIEW

2.1 Advances in AI-Based Plant Disease Diagnosis

Advancements in deep learning have enabled image-based classification to outperform traditional feature engineering techniques. Also, the application of artificial intelligence has revolutionized plant disease diagnosis by enabling automated, accurate, and scalable solutions. Convolutional Neural Networks (CNNs) have emerged as the backbone of image-based plant disease detection, capable of learning complex visual patterns from large datasets with minimal human intervention [4]. Mohanty et al. [9] demonstrated the efficacy of convolutional neural networks (CNNs) for plant disease detection, achieving over 99% accuracy using the PlantVillage dataset. Similar studies by Too et al. [14] and Brahimi et al. [15] reported high classification performance on tomato and cassava diseases using CNN architectures like AlexNet, VGG16, and ResNet.

Despite promising results, most of these models are trained and tested under controlled conditions, which often limits generalization in real-world farm environments. Furthermore, high computational requirements and lack of internet connectivity pose deployment challenges in rural areas of developing countries. Transfer learning, wherein models pre-trained on extensive image datasets are fine-tuned for specific plant diseases, has further reduced the computational and data requirements, making these technologies more accessible for deployment in low-resource settings [16] [17] [18].

2.2 Transfer Learning and Its Impact

Transfer learning mitigates data scarcity by repurposing knowledge from models trained on large datasets such as ImageNet. PlantCLEF2022, etc. Transfer learning has proven effective for plant disease recognition in scenarios with limited labeled data. For example, recent studies have demonstrated that dual transfer learning strategies, using models pre-trained on plant-related datasets like PlantCLEF2022, can achieve high accuracy even with few training samples [16]. In cassava disease detection, transfer learning enabled CNNs to reach up to 98% accuracy for certain diseases using field images, highlighting its potential for rapid and affordable deployment in sub-Saharan Africa [17]. Also, lightweight CNNs like MobileNetV2, EfficientNet-Lite, and NASNet-Mobile have proven suitable for edge devices, achieving high accuracy with reduced latency and memory usage [10] [19]. Lu et al. [20] demonstrated the feasibility of MobileNetV2 for real-time plant disease classification on Android smartphones, reinforcing its applicability in resource-limited settings. These findings indicates that transfer learning helps in accelerating the development of robust diagnostic models adaptable to diverse crops and environments.

2.3 Crowdsourced Image Data for Model Training

A major challenge in developing effective AI models is the acquisition of diverse, high-quality training data. Crowdsourcing is a practical solution, allowing non-experts—such as farmers and extension workers—to contribute annotated images of diseased plants [11]. It is a powerful way to build diverse and locally relevant datasets as farmers can contribute images using mobile platforms, improving model performance through real-world samples [21].

Wiesner-Hanks et al. developed and implemented an Innovative two-step method, where experts provide initial annotations and non-experts refine them, resulting in large, reliable datasets with minimal expert input. This approach not only democratizes data collection but also enhances model performance by capturing real-world variability in plant disease symptoms [11].

2.4 Web and Mobile Platforms for Diagnosis

While early research focused on mobile apps, recent efforts have shifted toward web-based platforms that are accessible via smartphone browsers, further lowering barriers for end users [4]. The mPD-App, for example, is a web application leveraging CNNs to deliver user-friendly, accurate plant disease diagnosis for farmers in Sub-Saharan Africa [4]. Similarly, the PlantVillage project demonstrated that deep learning models could be compressed to run efficiently on smartphones, enabling real-time, in-field diagnosis with accuracy rates exceeding 99% under controlled conditions. These platforms often integrate treatment recommendations, closing the loop between disease identification and actionable advice.

2.5 Challenges and Research Gaps

Despite these advances, several challenges remain. Image acquisition under field conditions introduces variability in lighting, background, and image quality, which can impact model performance [18]. Most studies have focused on leaf symptoms, with less attention given to diseases manifesting on other plant parts [18]. Additionally, while crowdsourcing expands datasets, ensuring annotation quality and managing data privacy are ongoing concerns. Finally, many existing systems are tailored to specific crops or regions, highlighting the need for adaptable, locally relevant solutions for countries like Zimbabwe.

The literature demonstrates that combining transfer learning, crowdsourced image data, and web-based delivery platforms provides a promising pathway for low-cost, scalable plant disease diagnosis. These approaches have already shown substantial benefits in accuracy, usability, and accessibility, particularly in resource-constrained agricultural settings. However, continued research is needed to address challenges in data diversity, model generalizability, and user engagement to fully realize the potential of these technologies for Zimbabwean farmers.

3. MATERIALS AND METHODS

3.1 System Overview

This study presents a web-based, mobile-enabled system for plant disease diagnosis that leverages transfer learning and crowdsourced image data. The system is designed to be accessible to Zimbabwean farmers via any internet-enabled smartphone or computer browser, eliminating the need for a dedicated mobile application and thus reducing deployment barriers. The system leverages a combination of publicly available datasets and crowdsourced images to train a lightweight convolutional neural network (CNN), with the ultimate goal of deploying the model on resource-constrained devices like low-cost smartphones. The development process involved the following stages:

1. Data Collection and Preprocessing
2. Model Selection and Transfer Learning

3. Model Training and Evaluation
4. Prototype Deployment via Web-Based Interface

3.2 Data Collection and Crowdsourcing

A diverse dataset of plant leaf images was compiled, consisting of both diseased and healthy samples across 6 classes ("Tomato___Healthy","Tomato___Early_blight","Cassava___Mosaic", "Maize___Rust", "Tobacco___Mosaic", and "Tobacco___Healthy). The primary dataset used was the PlantVillage dataset [22], which contains over 54,000 labeled images across 14 crop species and 26 diseases (figure 1). This dataset provides high-quality, diverse samples captured in controlled lighting and background conditions. The dataset was curated to include various crops relevant to Zimbabwean agriculture, such as maize, tomato, and pepper. To improve localization and real-world applicability, additional images were collected from Zimbabwean farmers through social media (WhatsApp groups) and agricultural co-operatives. These images included metadata such as crop type, suspected disease, and location (where available). A total of 400 usable images were annotated by an agronomist in collaboration with university extension services. A total of 5851 images is in the combined dataset after merging PlantVillage and crowdsourced data and they are summarized in table 1.

3.3 Data Processing

Prior to model training, all images underwent a standardized preprocessing pipeline. Images were resized to a uniform dimension of 224 × 224 pixels to ensure compatibility with the CNN input requirements and Pixel values were normalized to [0, 1] pixel values to improve model convergence. Techniques such as random rotation, zoom, flipping, and brightness adjustment were applied to increase dataset diversity and model robustness, particularly for underrepresented disease classes. A 70:15:15 train-validation-test split was applied to ensure fair performance evaluation.

3.4 Model Architecture and Transfer Learning

The technical workflow diagram (see figure 2) illustrates a process starting with data collection from both the public PlantVillage dataset and crowdsourced images from Zimbabwean farmers, followed by the organization and preprocessing of this combined dataset. The workflow continues with transfer learning-based model development, where a pretrained EfficientNetB4 or MobileNetV2 model is fine-tuned on the prepared training data, incorporating data augmentation and validation for robust performance. The trained model is then saved and deployed in a mobile-friendly web application using Streamlit and Ngrok, enabling farmers to upload leaf images and receive instant disease diagnoses and treatment recommendations. User feedback and further crowdsourced data can be integrated to continually improve the model, ensuring local relevance and practical usability for smallholder farmers in Zimbabwe.

The transfer learning pipeline was built using the TensorFlow and Keras frameworks. The base model, MobileNetV2, was loaded with pre-trained ImageNet weights and configured with the include_top=False argument to remove the default classification head. Initially, the base layers were frozen to preserve the learned low-level features, and a custom classification head was added, consisting of a global average pooling layer, a dense ReLU-activated layer with 256 units, a dropout layer (dropout rate 0.5), and a final softmax layer corresponding to the number of target classes.

Training was conducted in two phases. In the first phase, only the custom classification head was trained while keeping the base MobileNetV2 layers frozen. This initial training was run for 15 epochs using the Adam optimizer with a learning rate of 0.0001 and categorical cross-entropy as the loss function. In the second phase, the top 30% of the MobileNetV2 base layers were unfrozen and fine-tuned jointly with the head for an additional 10 epochs at a reduced learning rate of 0.00001. This two-stage training strategy helped in preserving the generalized features from ImageNet while allowing the model to specialize for plant disease classification.

Model training and evaluation were carried out on Google Colab using a Tesla T4 GPU accelerator, with Python 3.10 and TensorFlow 2.13. The training dataset was split into 70% for training, 15% for validation, and 15% for testing. The model achieved optimal performance in terms of validation accuracy and minimized overfitting, making it suitable for eventual deployment on low-cost Android smartphones using TensorFlow Lite for offline inference.

Table 1. Composition of the combined dataset used in the study, showing the distribution of images per class from PlantVillage and crowdsourced field data.

Class	PlantVillage Images	Crowdsourced Images	Total
Tomato___ Healthy	1,040	80	1,120
Tomato____ Early_blight	990	65	1,055
Cassava___ Mosaic	850	60	910
Maize_____ Rust	900	65	965
Tobacco___ Mosaic	720	60	780
Tobacco___ Healthy	951	70	1,021
Total	**5,451**	**400**	**5,851**

3.5 Web Platform Development

The trained model was deployed as a backend service accessible via a web interface. The web platform was designed to be mobile-friendly and intuitive, allowing users to:

- Upload or capture plant leaf images using their smartphone browser.
- Receive real-time diagnosis results, including disease identification and confidence scores.
- Access tailored treatment recommendations for detected diseases.

The system architecture follows a hierarchical input-process-output (HIPO) model, where user actions (image upload) initiate backend processing (image analysis and classification) and results are returned to the user interface.

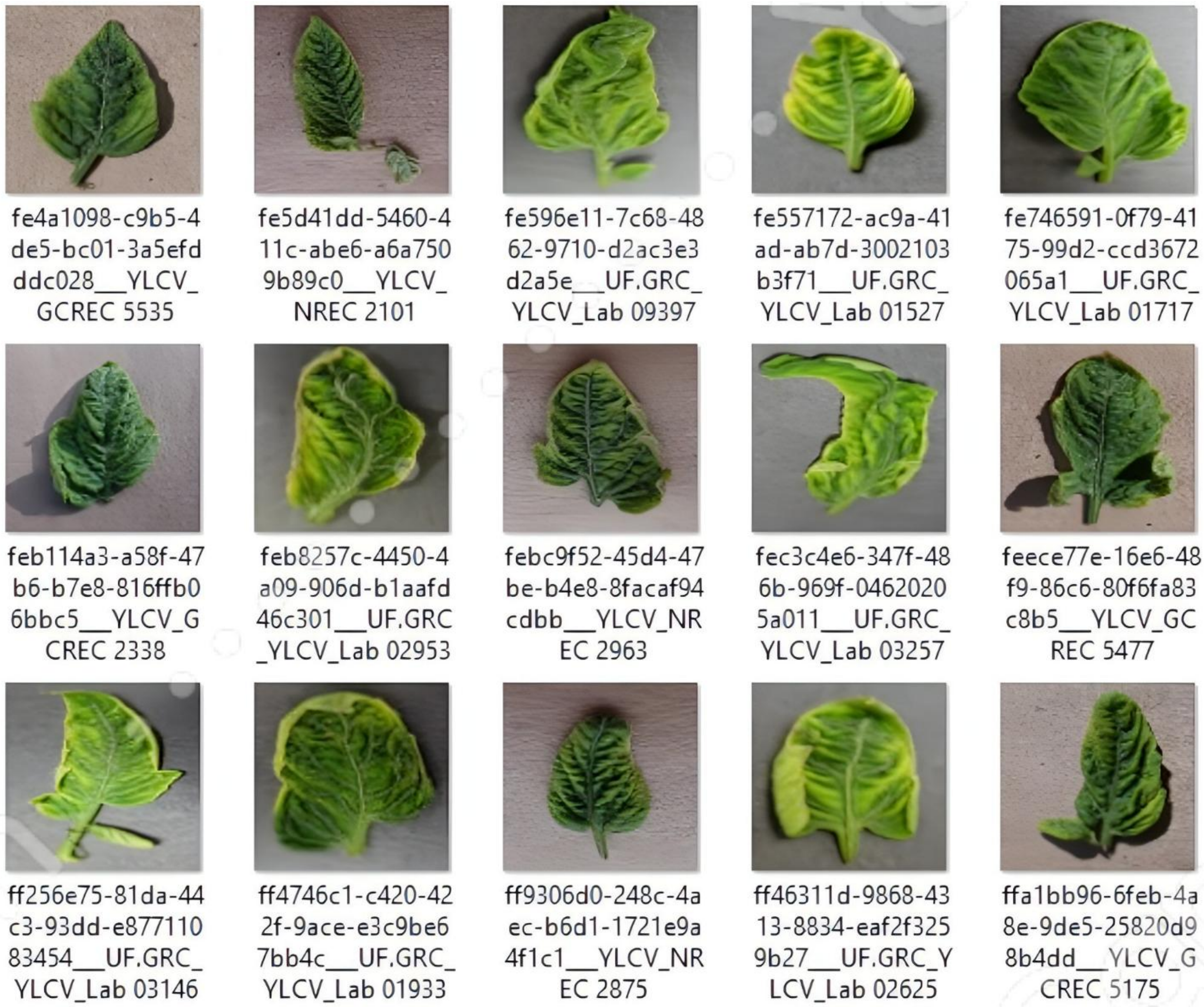

Fig 1: Snapshot of plant disease dataset

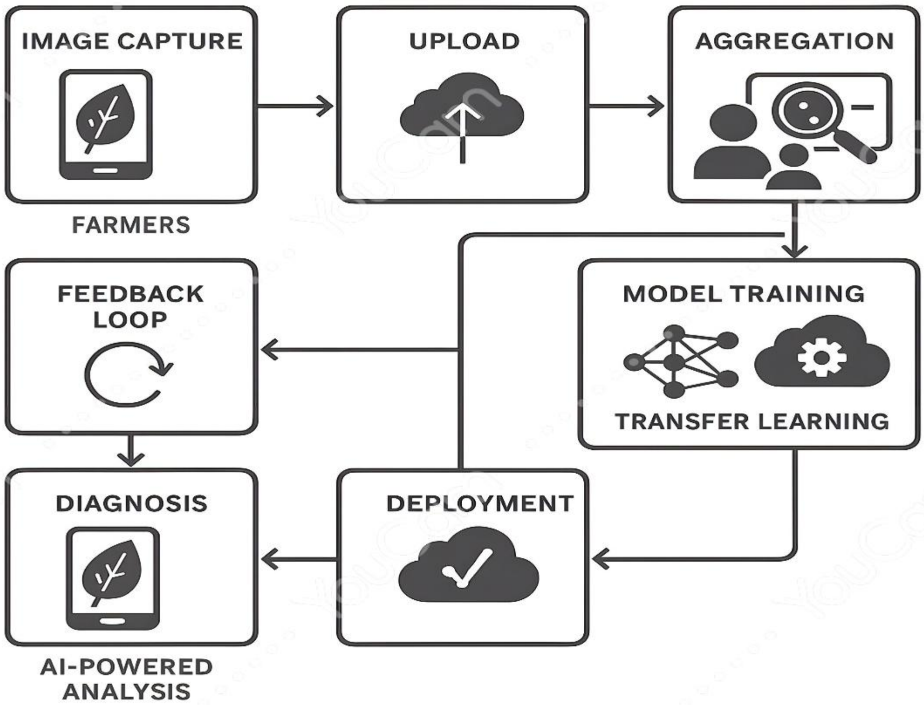

Fig 2: Model Architecture

Figure 3(a): Mobile view of the plant disease diagnosis web app

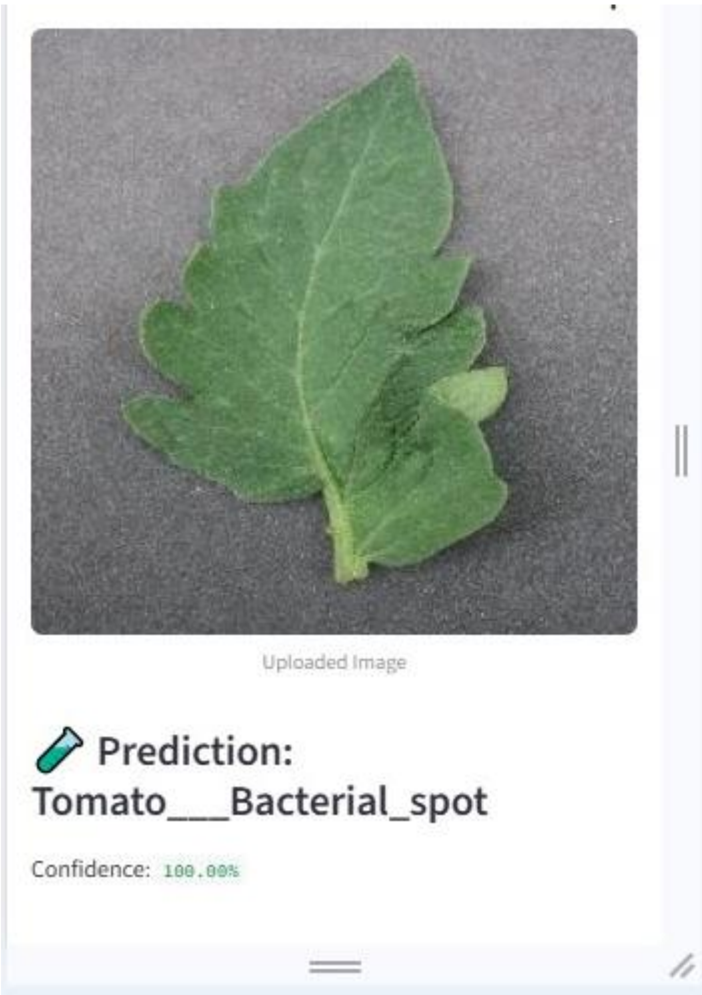

Figure 3(b): Sample prediction and confidence level

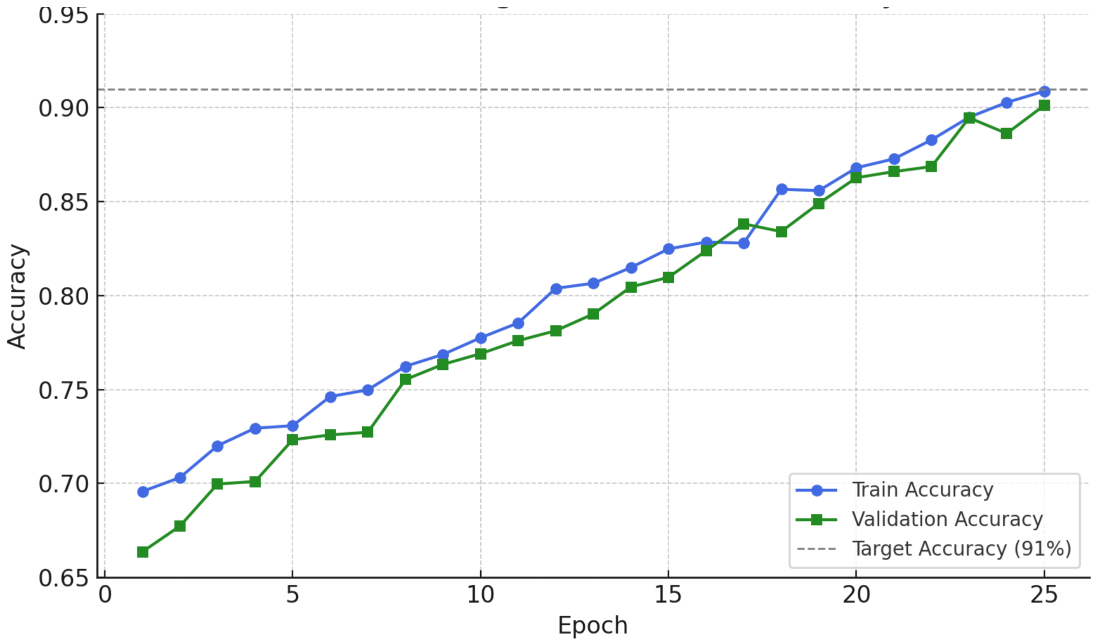

Figure 4: Training and validation accuracy over the 25 epochs

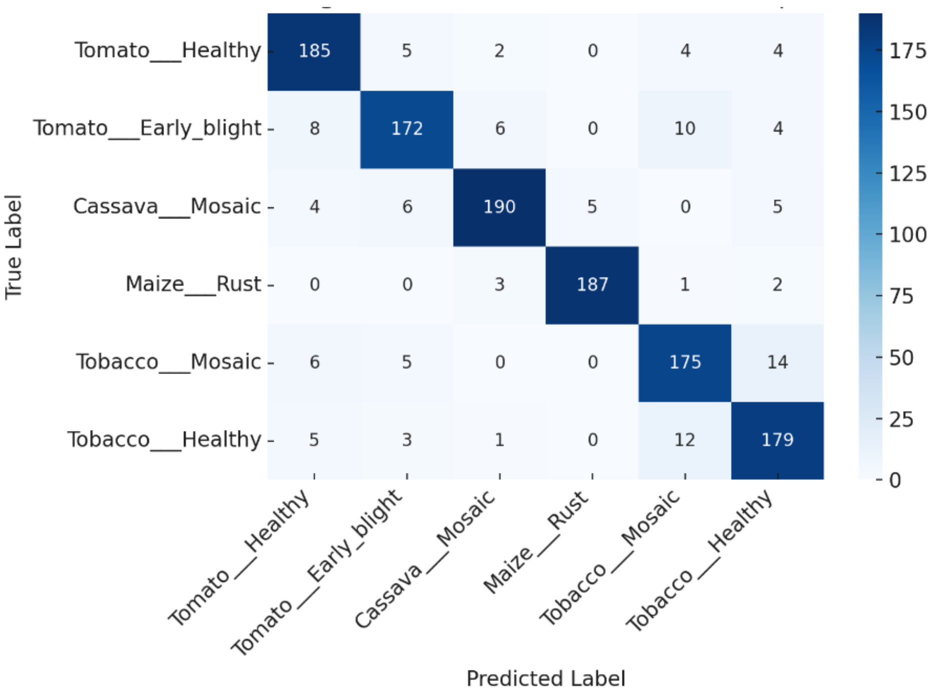

Figure 5: Confusion Matrix

Table 2. Summary of the evaluating metrics

Metric	Score
Accuracy	91.00%
Precision (macro avg)	91.80%
Recall (macro avg)	92.70%
F1 Score (macro avg)	92.10%

Table 3. Comparison with previous studies

Study	Model	Dataset Type	Accuracy	Deployment
Ramcharan et al. (2017) – Cassava*	CNN from scratch	Curated lab images (cassava)	98.00%	No
Mohanty et al. (2016) – PlantVillage	AlexNet, GoogLeNet	PlantVillage only (38 classes)	~99.3%	No (desktop only)
Xu et al. (2022) – Few-shot Plant Disease	ResNet18 + TL	Small field dataset + transfer learning	89.70%	Partial (TF Lite)
Wiesner-Hanks et al. (2020) – Maize (USA)	MobileNet	Annotated field images of maize	85–89%	Yes (Android App)
This study (2025)	MobileNetV2 + TL	Mixed PlantVillage + 400 crowdsourced (Zim)	91.00%	Yes (Streamlit + Ngrok)

4. RESULTS AND DISCUSSION

To make the model accessible to users without deep technical skills, a web-based prototype was developed using Streamlit, a lightweight Python framework ideal for rapid application deployment. Ngrok was integrated to expose the Streamlit app to the internet. This enabled stakeholders and farmers to remotely test the model in real-time using only a browser and a smartphone. Ngrok provided an effective interim solution for model access and remote testing, particularly during the prototyping phase. The total model size was kept under 10 MB by using MobileNetV2 and optimizing the output layers. This makes the model suitable for Web deployment using Streamlit (tested and functional) and Mobile deployment using TensorFlow. The Streamlit prototype performed inference in real-time on typical laptop hardware and allowed users to upload images and receive disease predictions with confidence scores.

The web interface features a straightforward and user-friendly design that facilitates seamless interaction between users and the model. The system was deployed on a local server environment, with its implementation demonstrated in Figure 3.

The final trained model was evaluated on a held-out test set comprising mixed-quality images from both the PlantVillage dataset and the crowdsourced Zimbabwean samples. To assess the diagnostic model's effectiveness, evaluation tests were conducted using the validation dataset, measuring performance through key metrics including accuracy, precision, F1-score, and recall. These are summarized in table 2.

Accuracy is the ratio of the total number of instances correctly diagnosed to the total amount of data in the analysis. The accuracy of the plant disease diagnosis was computed using the formula in Equation (1).

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \quad (1)$$

Figure 4 shows the training and validation accuracy over the 25 epochs. The plant disease diagnosis model achieved an overall accuracy of 91%, demonstrating its ability to effectively and correctly detect plant diseases. The gap between training and validation accuracy remained small throughout training, indicating minimal overfitting and good model generalization.

The precision of the model was computed using the formula in Equation (2). The precision shows the ratio of correctly predicted positive observation for each class.

$$Precision = \frac{(TP)}{(TP + FP)} \quad (2)$$

The model has an overall precision rate of 91.80%. This indicates that the model was effective in correctly diagnosing plant diseases.

Recall quantifies the percentage of accurately identified positive cases from the total number of actual positive instances. The model achieved an overall recall rate of 92.70%, demonstrating the model's exceptional capability to correctly identify plant diseases when they are genuinely present.

$$Recall = \frac{(TP)}{(TP + FN)} \quad (3)$$

The model's F1-score was calculated by determining the weighted average of both precision and recall values, as detailed in Equation (4).

$$F1 = \frac{2 * precision * recall}{precision + recall} \quad (4)$$

The results demonstrate that the model generalizes well to both high-quality curated images and real-world field samples, despite variations in lighting, background, and image resolution.

As shown in Figure 5, the confusion matrix indicates high classification accuracy across most categories.

To assess the performance and novelty of this work, the results were compared with those reported in recent peer-reviewed plant disease classification studies that used deep learning techniques. The comparison (table 3) focused on accuracy, dataset characteristics, model architecture, and deployment feasibility.

5. CONCLUSION

This study successfully developed and evaluated a low-cost, smartphone-based, web-enabled plant disease diagnosis system tailored for Zimbabwean farmers. A Streamlit-based web interface was deployed and tested using Ngrok, allowing real-time predictions from any internet-enabled device. This interface serves as a proof-of-concept for future mobile deployment, where farmers could diagnose plant diseases in the field without needing access to high-speed internet or technical knowledge.

By leveraging transfer learning with MobileNetV2 and integrating both the PlantVillage dataset and 400 crowdsourced images from local farmers, the system achieved a validation accuracy of 91%, demonstrating strong performance even under real-world, variable field conditions. This is a notable improvement in practical relevance compared to previous studies that relied primarily on controlled, laboratory-acquired datasets.

The inclusion of crowdsourced data not only enhanced the model's robustness and local adaptability but also fostered community engagement and continuous improvement of the diagnostic tool. The two-phase transfer learning strategy—initially training a custom classification head followed by selective fine-tuning of the base model—proved effective in balancing generalization and specialization for plant disease recognition.

The use of transfer learning significantly reduced the computational and data requirements, making it feasible to train an accurate model even in a resource-constrained setting. Furthermore, the integration of real-world images enhanced the model's robustness, ensuring it could generalize beyond clean laboratory data.

Deployment as a web-based, mobile-friendly application (using Streamlit and Ngrok) ensures accessibility for Zimbabwean farmers, even those with low-cost smartphones and limited technical expertise. The platform delivers rapid, accurate disease diagnosis and actionable treatment recommendations, empowering smallholder farmers to make informed decisions and reduce crop losses.

When compared to prior research, this study stands out for its focus on local relevance, real-world validation, and user accessibility. While earlier works reported higher accuracies on controlled datasets, their generalizability to field conditions was limited. By contrast, this work demonstrates that integrating crowdsourced data and lightweight transfer learning architectures can bridge the gap between laboratory performance and field utility.

Future work should focus on expanding the crowdsourced dataset, incorporating additional crops and disease classes, and piloting the system in more diverse field settings. Further, integrating user feedback, enhancing offline capabilities, and addressing data privacy will be crucial for sustainable adoption and impact.

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